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Dynamism in the Gender Wage Gap: Evidence from Pakistan

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I. INTRODUCTION

One of the main caveats of Pakistan's economic development history is the persistence of gender inequality with respect to almost all socioeconomic indicators. For instance, Pakistan ranks 66, out of 75 countries, with respect to the Gender Empowerment Measure (Human Development Report, 2006) with a GEM value of 0.377, largely a manifestation of very low estimated female to male earned income ratio, which is a depressing 0.29. GEM and other labour force statistics confirm the gender gap in labour force participation. One of the possible explanations of this gender gap is gender discrimination in the labour market, particularly in wages.

Evidence with respect to gender discrimination in Pakistan's labour market is well-documented. Siddique, *et al*. (2006), Nasir and Nazli (2000), Siddique, *et al*. (1998) and Ashraf and Ashraf (1993) all confirm that men earn higher wages than women even after controlling for measurable characteristics affecting their productivity. These studies, however, analyse the gender wage gap by comparing the mean male/female wage. Studies which compare the gender wage gap at different points along the wage distribution are not available for Pakistan.

This study aims to examine the evolution of the gender pay gap for the wage employed in Pakistan over the period covering 1996-97 to 2005-06. The primary objective of the current paper is to provide some clearer insights on the impact of the recent economic development on the gender pay gap. The contribution of the current paper, however, compared to previous research, is two-fold. First, our analysis covers a longer time period, almost a decade, given our use of data drawn from the Labour Force Survey at two distinct points in time: from LFS 1996-97, and then, after almost a decade, in 2005-06. Secondly, in contrast to the mean regression approach, we enhance the analysis by using a quantile regression approach [Albrecht, *et al.* (2003)], that allows us to explore the gender pay gap at selected points of the conditional wage distribution. This study provides the estimates of the temporal decomposition of the gender pay gap using both the mean and the quantile regression approach [Pham and Barry (2006)], which provides quantile measures of the gender wage at two specific points in time, 1997 and 2006, using respective Labour Force Surveys for each of these years. The analysis is further disaggregated by occupation, and province.

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The paper is organised as follows: Section II presents the literature review, including both the existing empirical evidence with regard to the gender wage gap in Pakistan, and also some international evidence on the pattern followed by the gender wage gap across the wage distribution, and the glass ceiling effect. Section III discusses the methodology; Section IV describes the dataset and provides descriptive statistics which inform us of especial features of female participation in the Pakistani labour market, including employment and wage ratio. Section V is a summary of the statistical findings of our analysis, while Section VI concludes by discussing the relevant policy implications.

II. LITERATURE REVIEW

Human capital theory of wage determination suggests that wages are tied to productivity, and in a non-discriminatory environment, the observed gender wage differential should be completely explained by differences in productivity between men and women. Gender discrimination occurs when equally productive male and female workers are paid differently. Given the gendered division of labour, women are considered less likely to invest in market-oriented formal education because they expect a shorter and more discontinuous working life; an investment in education will therefore not pay off well in the future. More limited experience and less investment in education will reduce their productivity and will translate in lower wages. However, as mentioned earlier, when equally productive male and female workers are paid differently this phenomenon is described as gender discrimination.

1. International Findings on Gender Pay Gap

Since Becker's (1957) seminal paper on the economics of discrimination, studies on the magnitude and sources of the gender wage gap have proliferated [Bayard, *et al.* (2003); Blau and Kahn (2000); Groshen (1991); OECD (2002)]. There is ample evidence of gender discrimination in a host of developed and developing countries. Newell and Reilly (2001) use the Oxaca-Blinder methodology to investigate the gender wage gap in former communist countries of eastern Europe and the Soviet Union; they find that most of the earnings gap in the 16 countries considered is ascribed to the 'unexplained' component. Further, the study uses the Quantile regression analysis to demonstrate that in all but one country considered, the ceteris paribus gender pay gap rises as we move up the wage distribution. Similar findings that confirm that the gender gap increases across the wage distribution and accelerates in the upper tail of the distribution are confirmed for European countries [see Albrecht, *et al.* (2001) for Sweden]. This acceleration in the wage gap at the upper tail is interpreted as the presence of a glass ceiling effect. Pereira and Martins (2000) used the quantile regression framework for an analysis of changes in the returns to education at distinct points of the log wage distribution for 15 European countries. The most recent Structure of Earnings Survey data for 2002, covering only the private sector, indicate a rather substantial pay gap between men and women. All in all, the gender pay gap in the 25 member states is almost 25 percent. The largest gap is found in the UK (30 percent), the smallest in Slovenia (11 percent).

Some studies using the semi-parametric technique of quantile regressions also exist for developing economies such as the Philippines (2004) and Vietnam (2006). These studies find a different pattern in the gender wage gap across the gender wage distribution. Sakellariou (2004) using the quantile regression find that the underpayment of women is much higher for low earnings workers and continuously decreases as we progress to higher earnings; they find that 'this underpayment at the lowest income decile is more than twice the underpayment at the highest income decile'. A similar pattern is confirmed for Vietnam [Pham and Reilly (2006)].

2. Gender Pay Gap in Pakistan

As mentioned above, the mean gender wage gap has been extensively studied in Pakistan. Ashraf and Ashraf (1993) estimated the mean gender wage gap for Pakistan as a whole and also for the four provinces. Using the Household Income and Expenditure Survey (HIES), the respective Mincerian Wage equations estimated separately for males and females confirmed that the earnings level rose monotonically with the level of educational attainment for both time periods considered (1979 and 1986), and for both sexes in most cases. They claimed that the wage gap stood at 63.27 percent in 1979, and declined to 33.09 percent in 1986. They found that the decline was broad-based and occurred in every province, and across every industrial group.

Siddique, *et al*. (1998) also find evidence for gender discrimination. They used the standard (Oaxaca 1973) decomposition method to split the gender wage gap into two parts: the part due to difference in characteristics and the part due to differences in return to these characteristics. The latter constitutes gender discrimination. Siddique, *et al*. estimate discrimination of 55–77 percent, i.e. 55 to 77 percent of the earnings differential between male and female workers is a result of discrimination in the labour market.

Nasir and Nazli (2000) used the 1995-96 Pakistan Integrated Household Survey (PIHS) to estimate the Mincerian wage equation. They estimate a positive and significant gender coefficient (0.264) after controlling for region (rural/urban), province, and educational attainment.

Siddique, *et al*. (2006) used the survey data of export oriented industries located in Karachi, Faisalabed and Sailkot: The results of the study are in line with other studies and confirm gender discrimination in export oriented industries. They further concluded that the impact of adjustment policies, leading to liberalisation, and resulting change in the labour market, has a disproportionately higher negative impact on females.

The studies mentioned above provide empirical support for gender discrimination in the Pakistani labour market; however, these studies analysed the gender wage gap by comparing the *mean* male/female wage. Studies which compare the gender wage gap at different points along the wage distribution are not available for Pakistan.

III. EMPIRICAL STRATEGY

To analyse the gender pay gap, we choose more than one method to verify the sensitivity of the gender wage differential with respect to the choice of technique. The estimates include a comparison of the mean male-female wage gap, the Oxaca-

Blinder decomposition of the male-female wage differential, and finally, an analysis of the gender wage gap along the wage distribution. In the context of the quantile regression approach, we largely relied on the temporal decomposition technique of Pham and Barry (2006).

1. Analysing the Gender Pay Gap

Perhaps the simplest approach to analysing the gender pay gap is to divide the mean value of female wage by the mean value of male wage:

$$\bar{D} = \frac{\bar{w}_f}{\bar{w}_m} \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad (1)$$

where w_f and w_m represent the wages of males and females, D represents discrimination or gender pay gap and the bar sign indicates averages.

2. The Dummy Approach

Following the seminal work of Mincer (1974), it is conventional to specify log wages as a function of a set of wage determining characteristics, which primarily include controls for human capital. In the empirical literature on the gender pay gap, the simplest way to analyse the gender pay gap is to perform a regression analysis, with gender included as a dummy variable, in order to capture the effect of discrimination:

$$Wi = \beta Xi + \gamma sexi + \varepsilon i \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad (2)$$

where w_i represents the log wage and X_i the control characteristics (e.g. education, job experience, and job characteristics) of an individual i, ß and γ are parameters.

3. The Oxaca—Blinder Decomposition

A relatively more sophisticated procedure to investigate the gender pay gap is developed by Blinder (1973) and Oaxaca (1973). In this procedure, wages are estimated separately for individuals, *i*, of the different groups, *g* (males and females). As a result, this procedure allows that productive characteristics of men and women are rewarded differently:

$$wi = \beta gXi + \varepsilon gi \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad (3)$$

where g = (m, f), represents the two sexes; Wgi is the log wage, and Xgi the control characteristics of an individual i of group g.

The total wage differential between men and women can then be decomposed into an explained part (differential due to differences in characteristics) and an unexplained residual.

The difference in mean wages can be written as:

$$D^A = W_m - W_f = (X_m - X_f)\hat{\beta}_m + (\hat{\beta}_m - \hat{\beta}_f)X_f \equiv E + U, \quad \dots \quad \dots \quad (4)$$

where Wg denotes the mean log wage, $X\ g$ represents the control characteristics of group g and $\hat{ß}g$ the estimated parameter from Equation (3). While the first term represents the effect of different productive characteristics (the endowment effect *E*), the second term represents the unexplained residual *U* (often referred to as 'wage discrimination') which includes differences due to unobserved variables that influence productivity and difference due to a differential reward for equal characteristics.

In Equation 4 the difference in male and female characteristics are evaluated using the male wage structure. In principle, it is possible to use the female wage structure as the reference. This will in general lead to different outcomes.

4. Temporal Decomposition Using Mean Regression

In the context of the mean regression framework, we can adopt an index number approach to temporally decompose the gender pay gap. Based on Equation 4, the overall gender pay gap, at separate points in time can be expressed as:

$$D_0^A = (X_{0m} - X_{0f})\hat{ß}_{0m} + (\hat{ß}_{0m} - \hat{ß}_{0f})X_{0f} \quad \dots \quad \dots \quad \dots \quad \dots \quad (5)$$

$$D_n^A = (X_{nm} - X_{nf})\hat{ß}_{nm} + (\hat{ß}_{nm} - \hat{ß}_{nf})X_{nf} \quad \dots \quad \dots \quad \dots \quad \dots \quad (6)$$

where 0 denotes the base year and *n* any year after the base year. The temporal decomposition of the gender pay gap can be expressed as:

$$D_n^A - D_0^A = (X_{nm} - X_{nf})\,\hat{\beta}_{nm} - (X_{0m} - X_{0f})\,\hat{\beta}_{0m} + (\hat{\beta}_{nm} - \hat{\beta}_{nf})\,X_{nf} - (\hat{\beta}_{0m} - \hat{\beta}_{0f})\,X_{0f}$$

or

$$\Delta D^A = \Delta X_n\,\hat{\beta}_{nm} - \Delta X_0\,\hat{\beta}_{0m} + \Delta\hat{\beta}_n\,X_{nf} - \Delta\,\hat{\beta}_0\,X_{0f} \quad \dots \quad \dots \quad \dots \quad (7)$$

After some arithmetic operations the temporal decomposition of the gender pay gap can be rewritten as:

$$\Delta D^A = (\Delta X_n - \Delta X_0)\,\hat{\beta}_{nm} + (\Delta\hat{\beta}_n - \Delta\,\hat{\beta}_0)X_{nf} + \Delta X_0\,\Delta\hat{\beta}_m + \Delta\,\hat{\beta}_0\,\Delta X_f \quad \dots \quad (8)$$

Thus, the overall change in the gender pay gap between two years can be decomposed into four parts. The first part is attributable to the temporal change in the gender differential in realisation of observable characteristics using the male coefficient. The second part is attributable to the temporal change in the realisation of the observable female characteristics. The third part is attributable to the temporal change in the male wage structure. The final term is attributable to the temporal change in unequal treatment (or wage discrimination).

5. Analysing Gender Discrimination Using Quantile Regressions

The foregoing decompositions are situated within a mean regression framework. An exclusive focus on the mean, however, provides an incomplete account of the gender pay gap. The quantile regression approach allows the gender pay gap to be estimated at particular quantiles of the conditional wage distribution as opposed to simply the mean. The estimation of a set of conditional quantile functions potentially allows a more detailed portrait of the relationship between the conditional distribution of the wage and selected covariates. In contrast to the OLS approach, the quantile regression procedure is arguably less sensitive to outliers and provides a more robust estimator in the face of departures from normality than the OLS technique [Koenker (2005); Koenker and Basset (1978)]. In addition, according to Deaton (1997), quantile regression models may also have better properties than the OLS ones in the presence of heteroscedasticity. Using this methodology, the log wage equation may be estimated conditional on a given specification and then calculated at various percentiles of the residuals (e.g., 10th, 25th, 50th 75th or 90th) [see Chamberlain (1994)].

The quantile regression for both sex groups can be defined as:

$$W_g = X_g' ß_{\theta g} + \mu_{\theta g} \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (9)$$

where $Q_\theta (W_g \mid X_g) = X_g' ß_{\theta g}$ and $Q_\theta (\mu_{\theta g} \mid X_g) = 0,$ $ß_{\theta g}$ denotes the unknown male and female parameter vector for the θ^{th} quantile, and θ denotes the chosen quantile.

From Equation 9

$$Q_\theta (W_g) = E(X_g \mid W_g = Q_\theta (W_g))'ß_{\theta g} + E(\mu_{\theta g} \mid W_g = Q_\theta (W_g)) \quad \ldots \quad \ldots \quad (10)$$

In this expression, characteristics are evaluated conditionally at the unconditional quantile log wage value and not unconditionally as in the case of the mean regression approach. The term $E(\mu_{\theta g} \mid W_g = Q_\theta (W_g)$ is thus non-zero for both sex groups. From Equation (10), the gender pay gap at the θ^{th} quantile is defined as Δ_θ and this can be decomposed into three parts:

$$D_\theta = [E(X_m \mid W_m = Q_\theta (W_m)) - E(X_f \mid W_f = Q_\theta (W_f))]'\hat{ß}_{\theta m} + E(X_f \mid W_f = Q_\theta (W_f))'(\hat{ß}_{\theta m} - \hat{ß}_{\theta f}) + [E(\mu_{\theta m} \mid W_m = Q_\theta (W_m)) - E(\mu_{\theta f} \mid W_f = Q_\theta (W_f))] \quad (11)$$

This can be rewritten more compactly as:

$$D_\theta = \Delta O_\theta'\hat{ß}_{\theta m} + O_{\theta f}'\Delta\hat{ß}_\theta + \eta_\theta \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (12)$$

where $\Delta O_\theta = O_{\theta m} - O_{\theta f} = E(X_m \mid W_m = Q_\theta (W_m)) - E(X_f \mid W_f = Q_\theta (W_f))$,

$\Delta\hat{ß}_\theta = \hat{ß}_{\theta m} - \hat{ß}_{\theta f}$ and

$\eta_\theta = E(\mu_{\theta m} \mid W_m = Q_\theta (W_m)) - E(\mu_{\theta f} \mid W_f = Q_\theta (W_f))$

Using mean characteristics in Equation (12) may provide unrepresentative realisations for the basket of characteristics at points other than the conditional mean wage to which they actually relate. Therefore, it is necessary to use realisations for the basket of characteristics that more accurately reflect the relevant points on the conditional wage distribution. In this paper, to derive the characteristics at different quantiles of the wage distribution, the sampling variances for the quantile regression estimates are obtained using bootstrapping.

In the context of the quantile regression approach, we use a relatively ad hoc method for the temporal decomposition of the gender pay gap at selected quantiles [see Pham and Barry (2006) for details]. The overall gender pay gap at the qth quantile can be expressed as:

$$D_{\theta 0} = \Delta O_{\theta 0}'\hat{ß}_{\theta m0} + O_{\theta f0}'\Delta\hat{ß}_{\theta 0} + \eta_{\theta 0} \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (13)$$

$$D_{\theta n} = \Delta O_{\theta n}{}'\,\hat{ß}_{\theta mn} + O_{\theta fn}{}'\,\Delta\hat{ß}_{\theta n} + \eta_{\theta n} \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (14)$$

where 0 denotes the base year and *n* any year after the base year. The temporal decomposition of the gender pay gap is as follows:

$$D_{\theta n} - D_{\theta 0} = (\Delta O_{\theta n} - \Delta O_{\theta 0})'\,\hat{ß}_{\theta mn} + (O_{\theta fn} - O_{\theta f0})\,\Delta\hat{ß}_{\theta n} + \Delta O_{\theta 0}{}'(\hat{ß}_{\theta mn} - \hat{ß}_{\theta m0})$$
$$+\, O_{\theta f0}\,(\Delta\hat{ß}_{\theta n} - \Delta\hat{ß}_{\theta 0}) + (\eta_{\theta n} - \eta_{\theta 0}) \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (15)$$

Thus, the overall change in the gender pay gap between two years at the θ^{th} quantile can be decomposed into five parts. The first part is attributable to the temporal change in the gender differential in realisations of observable characteristics at the θ^{th} quantile of the wage distribution evaluated using male coefficients. The second part is attributable to the temporal change in the realisations of the observable female characteristics at the θ^{th} quantile of the wage distribution. The third part is attributable to the temporal change in the male wage structure at the θ^{th} quantile of the wage distribution. The fourth term is attributable to the temporal change in unequal treatment (or wage discrimination) at the θ^{th} quantile of the wage distribution. The final term is unexplained and may be attributable to the changing role of un-observables over time.

The temporal decomposition suggested by Juhn, Murphy and Pierce (1991) could be used to decompose the average pay gap over time but this procedure is neither outlined nor pursued here in terms of the mean regression analysis. The Equation 15 is subject to an 'index number' problem, the temporal gender pay gap can also be re-cast in another form. However, in this paper we restricted ourselves to Equation 15.

IV. DATA AND SPECIFICATION ISSUES

Respective Labour Force Surveys for 1996-97 and 2005-06 are employed for our analysis. These surveys provide a narrative of almost a decade. The survey collects comprehensive information on various activities of workers. The information about employment status and distribution of employed labour force by industry division, gender and regions is particularly important for this study. A comparison of LFS with other data sources shows the superiority of LFS because of greater internal and external consistencies [Zeeuw (1996)]. Since the 1990s, the questionnaire of the LFS has been revised twice and a number of other changes have been made to improve the quality of data collection as well as coverage of different sub-groups.

For the purpose of our analysis we restrict our sample to wage earners and salaried persons of 10 to 70 years of age: for 2005-06 the sample contains 24,366 individuals, 21,323 males and 3,043 females; while for the 1996-97 cross-section the 13,594 individuals, 12,229 males and 1,365 females. The majority of these individuals are full-time employees who work more than 35 hours per week. The data on earnings include only cash payments; other benefits such as bonuses are not included in these earnings.

1. Specification Issues

The wage regression analysis reported in this study uses monthly real wage rates. The natural logarithms of these real wage rates are then used in the augmented Mincerian wage equations, which control for, inter alia, human capital and other characteristics. It is customary to use a years-in-education variable in the standard human capital wage specification. In case of Pakistan, the schooling years would have to be computed from the information on the highest educational qualifications obtained as reported in the household surveys. However, as demonstrated in other studies, this might introduce noise into the measurement of this particular variable [for instance Pham and Barry (2006), Sabir and Aftab (2006)] and this study thus uses a set of educational dummies to capture human capital effects. In addition, the age of an individual is used to proxy for labour market experience rather than using a potential labour force measure. This is acknowledged as a constraint in this application but data limitations prevent use of a more accurate measure.

The econometric specification used in this study is slightly different from other studies on gender pay gap in Pakistan in a couple of key respects. Firstly, educational levels and the individual's age are used instead of years in schooling and potential experience. This is to avoid the introduction of a possible measurement error in key explanatory variables, though it is acknowledged that the use of age, a proxy experience measure, as compared to the use of an actual measure, is likely to inflate the magnitude of the unequal treatment component in the decompositions undertaken here. Secondly, occupation controls for the wage employed workers are not included in our regression models. This is a judgment call and we take the view that the inclusion of controls that may reflect the outcome of a labour market discriminatory process is undesirable in this case. In addition, there is also a concern regarding the potential endogeneity of the occupational attachment variables.

V. DESCRIPTIVE STATISTICS

Pakistan's labour market is characterised by a very low female to male employment ratio of 0.14 in 2005-06 (see Table 1). In 1996-97 for every 9 men employed only one woman was working; in comparison, in 2006 for every 7 men employed only one woman is employed. Although female to male employment ratio has marginally improved since 1996-97, however, it still remains very low. The descriptive statistics further reveal a large and persistent wage gap between males and females. The gender wage ratio, over the last decade, has only posted a marginal increase from 0.66 to 0.69: In FY2006 for every Rs 1 earned by a man, a female worker earns only 69 paisas.

Table 1

Employment and Wage Ratios

	Employment Ratio			Wage Ratio		
	2005-06	1999-00	1996-97	2005-06	1999-00	1996-97
Pakistan	0.143	0.132	0.112	0.693	0.692	0.660
Punjab	0.212	0.201	0.186	0.616	0.632	0.584
Sindh	0.091	0.056	0.059	0.933	0.783	0.803
NWFP	0.089	0.099	0.061	0.901	0.984	0.914
Balochistan	0.038	0.039	0.029	0.918	0.946	0.909

Source: Authors estimates based on LFS 1996-67, 1999-00 and 2006-07.

Note: Employment ratios are computed by dividing number of employed female by number of employed males. Wage ratios are computed as defined in Equation 1.

Table 2 presents descriptive statistics for some of the relevant variables. The average age of employed males has consistently been higher than the mean age of working women: the mean age of working men in 1996-97 was 33.7, and has reduced to 32.7 years, in 2006; while the average age of working women remained unchanged at 30.7 years.

Table 2

Employed Labour Force Characteristics by Gender

	2005-06		1999-00		1996-97	
	Women	Men	Women	Men	Women	Men
age	30.654	32.758	32.820	33.001	30.675	33.681
Employed	3,043	21,323	1,280	9,711	1,365	12,229
primary	0.077	0.158	0.040	0.145	0.056	0.134
middle	0.038	0.123	0.030	0.109	0.039	0.102
matric	0.112	0.150	0.138	0.142	0.138	0.149
intermed	0.085	0.068	0.079	0.070	0.095	0.080
graduate	0.084	0.058	0.084	0.071	0.104	0.060
post_pro	0.094	0.052	0.073	0.056	0.070	0.053
public	0.246	0.252	0.303	0.316	0.360	0.342
urban	0.517	0.515	0.607	0.613	0.578	0.596
white_c*	0.062	0.082	0.120	0.106	0.251	0.124
blue_c**	0.927	0.901	0.863	0.881	0.692	0.854
Wage	3,943	5,691	2,599	3,754	2,296	3,478

Source: Authors estimates based on LFS 1996-67, 1999-00 and 2006-07.

*White colour jobs are defined as professional and managerial jobs.

**Blue colour jobs are defined as technical, clericals, crafts and other services related jobs.

If we look at the education attainment indicators for the employed sample, we find that, on average, women workers are more qualified than men, and yet remain under-paid, on average, as compared to their male counterparts. In 2006, while only 11 percent of the employed men were graduates, 17 percent of working women had a graduate degree. Finally, in 2006, the proportion of women in blue collar jobs (defined as technical jobs, clerks, crafts and other services related jobs) has increased as compared to 1997.

VI. EMPIRICAL RESULTS

The wage regression estimates, using the mean and the quantile regression models, are provided in the Appendix and are not the subject of detailed discussion here. However, it is noteworthy that the fit of the Mincerian equations have improved for both gender groups over the time period reviewed here and that the point estimates for the returns to the higher formal human capital measures have increased sharply. For instance, return to postgraduate has increased to 0.83 in 2005-06 as compare to 0.71 in 1999-2000 and 0.81 in 1996-97. This could be taken to reflect the enhanced role of the labour market in valuing human capital in Pakistan over the high economic growth period.

1. Gender Pay Gap: Pooled Regression

Table 3 reports ceteris paribus gender pay gap estimated over the 1996-97 to 2005-06 period using a pooled wage regression model with a gender intercept term. The estimates reflect the decline in the relative female wage position. For instance, in 1996-97

Table 3

Gender Pay Gap Based on Pooled Regression

Year	Mean	Q10	Q25	Q50	Q75	Q90
2005-06	0.6053	0.9388	0.7727	0.6036	0.4129	0.3303
	0.0126	*0.0220*	*0.0218*	*0.0181*	*0.0134*	*0.0319*
1999-2000	0.5334	0.7364	0.6381	0.4978	0.4059	0.3815
	0.0185	*0.0360*	*0.0294*	*0.0172*	*0.0204*	*0.0292*
1996-97	0.4969	0.7728	0.5922	0.4064	0.3481	0.3286
	0.0186	*0.0444*	*0.0472*	*0.0180*	*0.0170*	*0.0248*

Note: Estimates are based on Equation 2.
Standard errors are in italics. The OLS standard errors are based on Huber (1967) and the quantile regression model estimates are based on bootstrapping.

a male wage employee earned 50 percent more than a comparable female, on average and ceteris paribus, but by 1999-2000 the ‘mark-up’ had increased to 53 percent, exhibiting further worsening thereafter in 2006 to 60.5 percent.

Table 3 also provides the estimated gender effects at different quantiles of the conditional wage distribution. These estimates suggest mix pattern in the female relative wage position in the Pakistani labour market. The gender pay gap tends to display a sharp decline with movement across the conditional wage distribution. This tentatively suggests that gender pay inequality is larger in the low-paid than in the high-paid jobs though this is interrogated more closely using the decompositions reported below. The decreasing ceteris paribus gender pay gap across the different quantiles of the conditional wage distribution, however, is in marked contrast to what is commonly observed in other transitional and developed economies where a ‘glass-ceiling’ effect is evident at higher points on the conditional wage distribution [see Reilly (1999) and Newell and Reilly (2001)].

2. Gender Pay Gap: Oxaca – Blinder Decomposition

The estimation of separate wage equations allows for the implementation of the various gender pay gap decomposition methodologies both at the mean and selected quantiles. In reviewing the estimates reported in Table 4, the expansion in the gender pay gap between 1996-97 and the later years is again evident. In all years, the greater part of the gender pay gap is attributable to unequal treatment with respect to gender. Similarly, in accordance with the results reported in Table 3, which uses an intercept shift to capture gender, the treatment effect appears to grow across the selected quantiles of the conditional wage distribution.

There is a substantial expansion in the average gender pay gap over time. The raw gender pay gap expanded by 0.10 log points between 1996-67 and 2005-06. The expansion in the gender pay gap over these years is also evident at selected points on the conditional wage distribution, though it is more pronounced at the bottom rather than at the top end of the distribution (see Table 4).

Table 4

Oaxaca-Blinder Decomposed Gender Pay Gap

Mean	Mean	Q10	Q25	Q50	Q75	Q90
In 2005-06						
endowment effect	0.011	0.032	0.018	0.009	0.009	0.001
wage discrimination	0.603	0.858	0.724	0.595	0.491	0.418
Unobservable Effect	0.000	0.033	0.197	0.091	–0.145	–0.255
Estimated Pay Gap	0.614	0.923	0.940	0.695	0.355	0.164
In 1999-2000						
endowment effect	–0.016	–0.015	–0.013	–0.011	–0.013	–0.018
wage discrimination	0.537	0.616	0.613	0.572	0.486	0.425
Unobservable Effect	0.000	0.175	0.232	0.085	–0.183	–0.225
Estimated Pay Gap	0.520	0.777	0.831	0.645	0.290	0.182
In 1996-97						
endowment effect	0.023	0.063	0.043	0.020	–0.006	–0.025
wage discrimination	0.489	0.638	0.538	0.475	0.403	0.393
Unobservable Effect	0.000	0.197	0.254	–0.089	–0.163	–0.063
Estimated Pay Gap	0.513	0.898	0.835	0.406	0.234	0.306

Note: Estimates are based on Equation 4 for mean regression model and equation 12 for quantile regression models.

3. Temporal Decomposition of the Gender Pay Gap

As highlighted above, there is a substantial increase in the average gender pay gap over time. The raw gender pay gap expanded by 0.93 log points between 1999-00 and 2005-06. The expansion in the gender pay gap over these two years is also evident at selected points on the conditional wage distribution, though it is more pronounced at the bottom rather than at the top end of the distribution. In fact, the top end shows a decline in gender pay gap during the same period (see Table 5).

In order to get further insights the mean and the quantile gender pay gaps between 1999-00 and 2005-06 (i.e. between 1996-97 to 1999-00, and 1996-97 to 2005-06) are

Table 5

Temporal Decomposition of the Gender Pay Gap:
Mean and Quantile Regression Approach

	Mean	Q10	Q25	Q50	Q75	Q90
Change in Gender Pay Gap During 1999-00 to 2005-06						
Change in Observable Gender Differentials	0.023	0.031	0.021	0.020	0.025	0.026
Change in Observable Characteristics	0.049	0.232	0.075	0.002	–0.003	0.001
Change in Wage Structure	0.004	0.016	0.010	0.000	–0.003	–0.007
Change in Unequal Treatment	0.017	0.010	0.037	0.021	0.008	–0.008
Unobservable Effect	0.000	–0.142	–0.034	0.006	0.038	–0.030
Change in Pay Gap	0.093	0.146	0.109	0.049	0.065	–0.018
Change in Gender Pay Gap During 1996-67 to 1999-00						
Change in Observable Gender Differentials	–0.026	–0.061	–0.037	–0.012	0.007	0.011
Change in Observable Characteristics	–0.007	–0.089	–0.006	0.058	0.073	0.033
Change in Wage Structure	–0.013	–0.017	–0.019	–0.019	–0.015	–0.004
Change in Unequal Treatment	0.054	0.068	0.081	0.039	0.011	–0.001
Unobservable Effect	0.000	–0.022	–0.022	0.173	–0.020	–0.162
Change in Pay Gap	0.008	–0.121	–0.004	0.240	0.056	–0.124
Change in Gender Pay Gap During 1996-67 to 2006-07						
Change in Observable Gender Differentials	0.018	–0.022	–0.004	0.027	0.043	0.054
Change in Observable Characteristics	0.065	0.134	0.089	0.076	0.098	0.047
Change in Wage Structure	–0.030	–0.009	–0.021	–0.038	–0.028	–0.029
Change in Unequal Treatment	0.049	0.086	0.098	0.044	–0.010	–0.022
Unobservable Effect	0.000	–0.164	–0.056	0.179	0.018	–0.192
Change in Pay Gap	0.101	0.025	0.105	0.289	0.121	–0.142

Note: Estimates are based on Equation 8 for mean regression model and Equation 15 for quantile regression models.

decomposed using both expressions (8) and (15). The change in observable characteristics like education level, employment in white or blue collar jobs and residence urban areas at the mean account for most of the expansion in the gender pay gap during 1999-00 to 2005-06. While from 1996-97 to 1999-00, observable characteristics, observable gender differentials and wage structure show a contraction the unequal treatment between the sexes accounts for the marginal expansion in the gender pay gap. To consolidate, the entire 9 year period, since 1996-97 to 2005-06, expansion in observable characteristics in the first half, and increased gender discrimination post 2000 account for the expansion in the gender pay gap.

At the bottom end of the wage distribution the gender pay gap expanded by 0.146 log points during 1999-00 to 2005-06, with changes in observable characteristics exerting an important widening role. However, from 1996-97 to 1999-00, bottom end of the wage distribution experienced a substantial contraction of 0.121 log points. At the top end of the wage distribution the gender pay gap contracted by 0.142 log points from 1996-97 to 2005-06 with changes in gender discrimination and wage structure exerting an important narrowing role. The change in the unobservable effect appears important in explaining the contraction in the gap over time at the 90th percentile. The increase in unequal treatment of men and women appears an important driver for the expansion in gender pay gap at the 10th and 25th quantile, and the median. Thus, the underlying narrative regarding the expansion of the gender pay is sensitive to the selected point on the conditional wage distribution.

VII. CONCLUSION

The recent economic performance has had a significant impact on the labour market in Pakistan. The statistics reveal that this high growth period successfully attracted more females than male workers into the labour market through providing more opportunities to them and reducing their unemployment rate. However, this increase in female labour supply translated in widening the gender pay gap.

A contribution of this paper has been the examination of the degree to which the gender pay gap varies across the conditional wage distribution. The decomposition analysis suggests that, in contrast to general perception, the absolute wage gap increase over the wage scale. In comport with the mean regression findings, there has been a contraction in the gender pay gap at the top end of the wage distribution. The change in unobservable characteristics appears important in explaining the contraction in the gap over time at the 90th percentile which is again resonant of our findings for the mean regression. However, the reduction in unequal treatment of men and women only appear an important driver for the increased gender pay gap in the lower-middle part of the conditional wage distribution.

We believe our analysis provides an informative portrait of the gender pay gap over time in the wage employment sector. But note, this sector only comprises 37.3 percent of those at work in Pakistan by 2005-06. It should be stressed, therefore, that this study thus offers only a partial insight into the effect of labour market dynamism in Pakistan. The sizeable increase in the gender wage gap among the wage employed is not a welcome feature of the transformation process. However, this finding should not be over-emphasised and some perspective is clearly required here. For instance, our analysis did not examine the dynamism on other important employment sectors (e.g., the self-employed or those employed in the informal sector) or the implications for those women discouraged from retaining links with the formal labour market.

ANNEX

Table A

Definitions of Explanatory Variables

Variable	Description
age	Age in years
Age^2	Square of Age
Gender	value 1for man, otherwise 0
Primary	value 1 if the highest level of education is primary, otherwise 0
Middle	value 1 if the highest level of education is middle, otherwise 0
Matric	value 1 if the highest level of education is matric, otherwise 0
Intermed	value 1 if the highest level of education is intermediate, otherwise 0
Graduate	value 1 if the highest level of education is graduation, otherwise 0
Post_pro	value 1 if the highest level of education is either post graduation or professional education, otherwise 0
Public	value 1 if employed in a government department, otherwise 0
Urban	value 1 if living in urban area, otherwise 0
White_c	value 1 if working as a professional (teacher, lawyers) or managerial position
Blue_c	value 1 if working as a technical or clerical position, or working in crafts and other services related jobs

Table B

Pooled Regression Model, 2005-06

Variable	Mean	Q10	Q25	Q50	Q75	Q90
age	0.0563	0.0852	0.0648	0.0477	0.0478	0.0433
	0.0017	*0.0044*	*0.0021*	*0.0017*	*0.0016*	*0.0026*
age2	–0.0006	–0.0010	–0.0007	–0.0005	–0.0005	–0.0004
	0.00002	*0.00006*	*0.00003*	*0.00002*	*0.00002*	*0.00004*
gender	0.6053	0.9388	0.7727	0.6036	0.4129	0.3303
	0.0126	*0.0220*	*0.0218*	*0.0181*	*0.0134*	*0.0319*
primary	0.0796	0.0838	0.0964	0.0831	0.0755	0.0565
	0.0126	*0.0276*	*0.0189*	*0.0121*	*0.0110*	*0.0175*
middle	0.1539	0.1827	0.1448	0.1346	0.1361	0.1412
	0.0141	*0.0249*	*0.0142*	*0.0096*	*0.0077*	*0.0170*
matric	0.2442	0.2623	0.2267	0.2314	0.2501	0.2525
	0.0132	*0.0233*	*0.0137*	*0.0101*	*0.0104*	*0.0172*
intermed	0.3712	0.3369	0.3563	0.3613	0.3909	0.4559
	0.0179	*0.0207*	*0.0159*	*0.0120*	*0.0127*	*0.0180*
graduate	0.6221	0.4745	0.4861	0.5817	0.6741	0.7419
	0.0196	*0.0306*	*0.0272*	*0.0234*	*0.0286*	*0.0291*
post_pro	0.8327	0.5796	0.7015	0.8313	0.8821	0.9510
	0.0219	*0.0513*	*0.0229*	*0.0133*	*0.0235*	*0.0502*
public	0.3267	0.5313	0.4333	0.3441	0.2005	0.0846
	0.0113	*0.0139*	*0.0119*	*0.0075*	*0.0105*	*0.0180*
urban	0.1182	0.1232	0.1181	0.0980	0.1004	0.0800
	0.0085	*0.0146*	*0.0093*	*0.0046*	*0.0070*	*0.0132*
white_c	0.4469	0.2657	0.3075	0.5048	0.6333	0.5961
	0.0371	*0.0835*	*0.0618*	*0.0342*	*0.0525*	*0.1098*
blue_c	0.1095	0.1665	0.1267	0.1331	0.1318	0.0158
	0.0330	*0.0896*	*0.0574*	*0.0281*	*0.0464*	*0.1200*
_cons	6.1754	4.6519	5.5720	6.3404	6.8287	7.4018
	0.0441	*0.1274*	*0.0841*	*0.0418*	*0.0517*	*0.1124*
Adj R-squared	0.398	0.2392	0.2579	0.267	0.2782	0.2895
Number of Obs	24366	24366	24366	24366	24366	24366

Note: Standard errors are in italics. The OLS standard errors are based on Huber (1967) and the quantile regression model estimates are based on bootstrapping.

Table C

Pooled Regression Model, 1999-00

Variable	Mean	Q10	Q25	Q50	Q75	Q90
age	0.0665	0.0992	0.0654	0.0542	0.0461	0.0471
	0.0025	*0.0048*	*0.0049*	*0.0032*	*0.0025*	*0.0037*
age2	–0.0008	–0.0012	–0.0008	–0.0006	–0.0005	–0.0005
	0.00003	*0.00007*	*0.00007*	*0.00004*	*0.00003*	*0.00005*
gender	0.5334	0.7364	0.6381	0.4978	0.4059	0.3815
	0.0185	*0.0360*	*0.0294*	*0.0172*	*0.0204*	*0.0292*
primary	0.0827	0.0472	0.0551	0.0775	0.0957	0.0865
	0.0187	*0.0301*	*0.0233*	*0.0195*	*0.0141*	*0.0191*
middle	0.1158	0.1113	0.1175	0.1035	0.1068	0.1281
	0.0210	*0.0347*	*0.0279*	*0.0191*	*0.0229*	*0.0239*
matric	0.2554	0.2468	0.2253	0.2168	0.2279	0.2533
	0.0192	*0.0284*	*0.0236*	*0.0211*	*0.0225*	*0.0191*
intermed	0.3248	0.3157	0.2901	0.2721	0.2999	0.3583
	0.0255	*0.0552*	*0.0347*	*0.0219*	*0.0325*	*0.0286*
graduate	0.5154	0.4037	0.3994	0.4399	0.4986	0.5552
	0.0275	*0.0397*	*0.0320*	*0.0323*	*0.0292*	*0.0484*
post_pro	0.7118	0.5202	0.5553	0.6012	0.6882	0.7978
	0.0326	*0.0310*	*0.0275*	*0.0376*	*0.0597*	*0.0702*
public	0.1259	0.3757	0.2625	0.1240	0.0337	-0.0589
	0.0151	*0.0233*	*0.0199*	*0.0166*	*0.0139*	*0.0135*
urban	0.1888	0.2138	0.1559	0.1728	0.1784	0.1661
	0.0124	*0.0218*	*0.0141*	*0.0063*	*0.0095*	*0.0191*
white_c	0.3558	0.1200	0.2867	0.4261	0.5783	0.5948
	0.0561	*0.0444*	*0.0455*	*0.0467*	*0.0558*	*0.0928*
blue_c	0.0659	-0.0309	0.0900	0.0923	0.1460	0.1003
	0.0510	*0.0340*	*0.0408*	*0.0389*	*0.0415*	*0.0986*
_cons	5.7713	4.4309	5.4217	6.0579	6.5075	6.8454
	0.0671	*0.1190*	*0.0990*	*0.0645*	*0.0671*	*0.1310*
Adj R-squared	0.3533	0.1959	0.1953	0.1871	0.209	0.2501
Number of Obs	10991	10991	10991	10991	10991	10991

Note: Standard errors are in italics. The OLS standard errors are based on Huber (1967) and the quantile regression model estimates are based on bootstrapping.

Table D

Pooled Regression Model, 1996-97

Variable	Mean	Q10	Q25	Q50	Q75	Q90
age	0.0607	0.0963	0.0649	0.0535	0.0438	0.0388
	0.0022	*0.0047*	*0.0030*	*0.0024*	*0.0030*	*0.0038*
age2	-0.0007	-0.0011	-0.0007	-0.0006	-0.0004	-0.0004
	0.00003	*0.00006*	*0.00004*	*0.00003*	*0.00004*	*0.00005*
gender	0.4969	0.7728	0.5922	0.4064	0.3481	0.3286
	0.0186	*0.0444*	*0.0472*	*0.0180*	*0.0170*	*0.0248*
primary	0.1111	0.1173	0.1071	0.0813	0.0862	0.0859
	0.0177	*0.0320*	*0.0257*	*0.0138*	*0.0159*	*0.0206*
middle	0.1605	0.1398	0.1970	0.1579	0.1661	0.1361
	0.0199	*0.0345*	*0.0256*	*0.0174*	*0.0172*	*0.0200*
matric	0.2174	0.2613	0.2353	0.1971	0.1914	0.1672
	0.0178	*0.0265*	*0.0189*	*0.0148*	*0.0142*	*0.0221*
intermed	0.3327	0.3288	0.2880	0.2844	0.2959	0.3222
	0.0232	*0.0275*	*0.0214*	*0.0176*	*0.0151*	*0.0328*
graduate	0.5583	0.4410	0.4778	0.4846	0.6175	0.6766
	0.0266	*0.0363*	*0.0294*	*0.0249*	*0.0341*	*0.0570*
post_pro	0.8183	0.5912	0.7186	0.7967	0.9065	0.9309
	0.0300	*0.0502*	*0.0368*	*0.0324*	*0.0271*	*0.0543*
public	0.0486	0.2686	0.1398	0.0229	-0.0772	-0.1440
	0.0139	*0.0199*	*0.0152*	*0.0133*	*0.0124*	*0.0182*
urban	0.1283	0.1074	0.1264	0.1358	0.1269	0.1422
	0.0116	*0.0157*	*0.0081*	*0.0095*	*0.0082*	*0.0159*
white_c	0.4164	0.4501	0.3351	0.3706	0.4204	0.4274
	0.0396	*0.0599*	*0.0423*	*0.0312*	*0.0404*	*0.0644*
blue_c	0.2136	0.3644	0.2192	0.1829	0.1906	0.0932
	0.0349	*0.0617*	*0.0339*	*0.0293*	*0.0394*	*0.0579*
_cons	5.7194	4.0956	5.2866	6.0255	6.5149	6.9840
	0.0500	*0.1165*	*0.0862*	*0.0564*	*0.0715*	*0.0979*
Adj R-squared	0.3043	0.2419	0.2175	0.1921	0.2102	0.2343
Number of Obs	13594	13594	13594	13594	13594	13594

Note: Standard errors are in italics. The OLS standard errors are based on Huber (1967) and the quantile regression model estimates are based on bootstrapping.

Table E

Female and Male Regression Model, 2005-06

	Female Sample only						Male Sample only					
Variable	Mean	Q10	Q25	Q50	Q75	Q90	Mean	Q10	Q25	Q50	Q75	Q90
Age	0.0307	0.0594	0.0308	0.0297	0.0261	0.0135	0.0607	0.0925	0.0697	0.0515	0.0478	0.0454
	0.0055	*0.0160*	*0.0092*	*0.0064*	*0.0087*	*0.0088*	*0.0017*	*0.0041*	*0.0021*	*0.0017*	*0.0021*	*0.0020*
age2	-0.0003	-0.0007	-0.0003	-0.0003	-0.0002	-0.0001	-0.0006	-0.0011	-0.0008	-0.0005	-0.0005	-0.0004
	0.00008	*0.00024*	*0.00012*	*0.00009*	*0.00014*	*0.00012*	*0.00002*	*0.00005*	*0.00003*	*0.00002*	*0.00003*	*0.00003*
Primary	0.0474	0.0621	-0.0388	0.0982	-0.0062	0.0321	0.0703	0.0891	0.0901	0.0738	0.0682	0.0442
	0.0533	*0.1170*	*0.0775*	*0.0557*	*0.0464*	*0.0948*	*0.0127*	*0.0264*	*0.0127*	*0.0110*	*0.0120*	*0.0224*
Middle	0.2085	0.1035	-0.1459	0.2607	0.3420	0.4499	0.1381	0.1836	0.1495	0.1250	0.1237	0.1177
	0.0730	*0.0995*	*0.0892*	*0.1304*	*0.0702*	*0.2170*	*0.0140*	*0.0236*	*0.0196*	*0.0121*	*0.0130*	*0.0179*
Matric	0.2446	0.1138	-0.0793	0.2702	0.3879	0.5603	0.2286	0.2670	0.2332	0.2210	0.2390	0.2170
	0.0496	*0.0694*	*0.0962*	*0.0632*	*0.0556*	*0.0621*	*0.0135*	*0.0264*	*0.0110*	*0.0089*	*0.0108*	*0.0204*
Intermed	0.3941	0.2466	0.2712	0.4525	0.5235	0.5618	0.3494	0.3341	0.3528	0.3432	0.3633	0.4039
	0.0559	*0.1083*	*0.0567*	*0.0571*	*0.0631*	*0.0521*	*0.0186*	*0.0179*	*0.0199*	*0.0122*	*0.0102*	*0.0237*
Graduate	0.6440	0.4565	0.5229	0.6526	0.7627	0.8588	0.5984	0.4573	0.4749	0.5434	0.6290	0.7197
	0.0569	*0.0880*	*0.0780*	*0.0683*	*0.0648*	*0.0700*	*0.0207*	*0.0321*	*0.0160*	*0.0185*	*0.0304*	*0.0316*
post_pro	0.8998	0.9890	0.7670	0.8352	0.8804	1.0356	0.7699	0.5003	0.6451	0.7719	0.8454	0.9302
	0.0621	*0.1331*	*0.0653*	*0.0527*	*0.0758*	*0.1015*	*0.0234*	*0.0294*	*0.0220*	*0.0241*	*0.0275*	*0.0510*
Public	0.7265	0.9467	0.9654	0.8457	0.5815	0.3161	0.2708	0.4988	0.4001	0.3016	0.1547	0.0516
	0.0399	*0.0931*	*0.0702*	*0.0453*	*0.0476*	*0.0483*	*0.0115*	*0.0137*	*0.0126*	*0.0098*	*0.0098*	*0.0153*
Urban	0.2031	0.2260	0.1669	0.1701	0.1577	0.1723	0.1041	0.1200	0.1146	0.0852	0.0836	0.0685
	0.0292	*0.0447*	*0.0506*	*0.0350*	*0.0338*	*0.0335*	*0.0087*	*0.0160*	*0.0073*	*0.0052*	*0.0071*	*0.0095*
white_c	0.5326	0.9658	0.7787	0.6182	0.4961	0.2551	0.4456	0.2365	0.2890	0.4908	0.6312	0.6018
	0.1441	*0.3968*	*0.3314*	*0.2003*	*0.1743*	*0.2721*	*0.0376*	*0.0821*	*0.0468*	*0.0435*	*0.0503*	*0.0646*
blue_c	-0.0895	0.6799	0.1784	-0.1398	-0.2721	-0.4404	0.1303	0.1748	0.1313	0.1362	0.1486	0.0503
	0.1282	*0.4002*	*0.3238*	*0.1916*	*0.1525*	*0.2364*	*0.0333*	*0.0724*	*0.0417*	*0.0308*	*0.0393*	*0.0538*
_cons	6.6656	4.5662	6.0537	6.7339	7.3555	8.1124	6.7073	5.4683	6.2633	6.8973	7.2413	7.6872
	0.1526	*0.4456*	*0.2975*	*0.2165*	*0.2177*	*0.2431*	*0.0440*	*0.0856*	*0.0529*	*0.0376*	*0.0381*	*0.0655*
Adj R-squared	0.4504	0.1671	0.2161	0.3066	0.3542	0.3333	0.3501	0.1733	0.2036	0.24	0.2679	0.2872
Number of Obs	3043	3043	3043	3043	3043	3043	21323	21323	21323	21323	21323	21323

Note: Standard errors are in italics. The OLS standard errors are based on Huber (1967) and the quantile regression model estimates are based on bootstrapping.

Table F

Female and Male Regression Model, 1999-2000

	Female Sample only						Male Sample only					
Variable	Mean	Q10	Q25	Q50	Q75	Q90	Mean	Q10	Q25	Q50	Q75	Q90
Age	0.0387	0.0328	0.0231	0.0240	0.0372	0.0383	0.0715	0.1065	0.0765	0.0571	0.0482	0.0517
	0.0080	*0.0201*	*0.0082*	*0.0086*	*0.0089*	*0.0088*	*0.0025*	*0.0047*	*0.0040*	*0.0027*	*0.0024*	*0.0035*
age2	-0.0004	-0.0004	-0.0002	-0.0002	-0.0004	-0.0004	-0.0008	-0.0013	-0.0009	-0.0006	-0.0005	-0.0005
	0.00011	*0.00025*	*0.00011*	*0.00013*	*0.00012*	*0.00012*	*0.00003*	*0.00006*	*0.00005*	*0.00004*	*0.00003*	*0.00005*
Primary	0.0806	0.0077	0.0602	0.0690	0.0268	-0.0648	0.0661	0.0368	0.0403	0.0727	0.0892	0.0764
	0.0959	*0.1356*	*0.0908*	*0.1075*	*0.0599*	*0.0897*	*0.0188*	*0.0349*	*0.0201*	*0.0210*	*0.0162*	*0.0256*
Middle	0.2894	-0.3204	0.0113	0.1823	0.4068	0.7426	0.0958	0.1054	0.1031	0.0897	0.0945	0.1054
	0.1087	*0.1828*	*0.1761*	*0.1366*	*0.1036*	*0.1689*	*0.0211*	*0.0333*	*0.0227*	*0.0144*	*0.0241*	*0.0166*
Matric	0.3466	0.0077	0.1661	0.3180	0.4054	0.4531	0.2232	0.2341	0.2033	0.1945	0.1906	0.2206
	0.0648	*0.1050*	*0.0837*	*0.0694*	*0.0596*	*0.0992*	*0.0199*	*0.0284*	*0.0209*	*0.0155*	*0.0195*	*0.0222*
Intermed	0.3530	0.0467	0.1669	0.3134	0.3930	0.4961	0.3083	0.3190	0.2854	0.2548	0.2806	0.3316
	0.0778	*0.1386*	*0.1009*	*0.0750*	*0.0712*	*0.1757*	*0.0267*	*0.0255*	*0.0221*	*0.0140*	*0.0226*	*0.0376*
Graduate	0.5918	0.3287	0.2963	0.4712	0.6160	0.9681	0.4952	0.4036	0.3861	0.4099	0.4961	0.5215
	0.0843	*0.1132*	*0.0645*	*0.0610*	*0.1009*	*0.2129*	*0.0288*	*0.0253*	*0.0244*	*0.0202*	*0.0431*	*0.0418*
post_pro	0.7649	0.3639	0.4516	0.7729	0.9072	1.1808	0.6953	0.4938	0.5410	0.5834	0.6681	0.7459
	0.0971	*0.1776*	*0.1084*	*0.0894*	*0.1251*	*0.2453*	*0.0343*	*0.0377*	*0.0318*	*0.0343*	*0.0492*	*0.0828*
Public	0.5414	1.1048	0.9626	0.6672	0.3425	0.0984	0.0663	0.3349	0.2022	0.0767	-0.0190	-0.0939
	0.0520	*0.0702*	*0.0625*	*0.0623*	*0.0623*	*0.0973*	*0.0157*	*0.0239*	*0.0215*	*0.0117*	*0.0119*	*0.0158*
Urban	0.1913	0.1356	0.1555	0.1921	0.1964	0.2089	0.1720	0.2036	0.1386	0.1494	0.1597	0.1683
	0.0419	*0.0686*	*0.0383*	*0.0346*	*0.0512*	*0.0786*	*0.0129*	*0.0227*	*0.0134*	*0.0085*	*0.0127*	*0.0110*
white_c	0.3324	0.0659	0.2381	0.1897	0.4422	0.7489	0.3318	0.1211	0.2866	0.3773	0.5627	0.5779
	0.1603	*0.1916*	*0.1539*	*0.1382*	*0.1971*	*0.5158*	*0.0594*	*0.0666*	*0.0898*	*0.0556*	*0.0711*	*0.0841*
blue_c	-0.1194	-0.2705	-0.1917	-0.1583	0.1017	0.3242	0.0799	0.0097	0.1333	0.0907	0.1314	0.0776
	0.1404	*0.1639*	*0.1191*	*0.1099*	*0.1284*	*0.4482*	*0.0542*	*0.0718*	*0.0935*	*0.0350*	*0.0505*	*0.0765*
_cons	6.3173	5.9192	6.2810	6.5699	6.5097	6.6115	6.2341	5.0195	5.8671	6.5444	6.9211	7.1848
	0.1955	*0.4089*	*0.1434*	*0.1400*	*0.1478*	*0.4334*	*0.0686*	*0.1207*	*0.1159*	*0.0500*	*0.0538*	*0.0839*
Adj R-squared	0.4621	0.2398	0.3053	0.3501	0.3265	0.3019	0.3099	0.2043	0.1925	0.1883	0.2175	0.2604
Number of Obs	1280	1280	1280	1280	1280	1280	9711	9711	9711	9711	9711	9711

Note: Standard errors are in italics. The OLS standard errors are based on Huber (1967) and the quantile regression model estimates are based on bootstrapping.

Table G

Female and Male Regression Model, 1996-97

	Female Sample only						Male Sample only					
Variable	Mean	Q10	Q25	Q50	Q75	Q90	Mean	Q10	Q25	Q50	Q75	Q90
Age	0.0412	0.0793	0.0454	0.0459	0.0324	0.0240	0.0637	0.0996	0.0676	0.0551	0.0452	0.0411
	0.0074	*0.0134*	*0.0149*	*0.0082*	*0.0093*	*0.0166*	*0.0023*	*0.0064*	*0.0027*	*0.0029*	*0.0040*	*0.0035*
age2	-0.0005	-0.0010	-0.0006	-0.0006	-0.0004	-0.0003	-0.0007	-0.0012	-0.0008	-0.0006	-0.0005	-0.0004
	0.00010	*0.00017*	*0.00022*	*0.00012*	*0.00013*	*0.00023*	*0.00003*	*0.00009*	*0.00004*	*0.00004*	*0.00006*	*0.00005*
Primary	0.0417	0.1000	-0.0061	-0.0640	0.1045	0.0167	0.1081	0.1135	0.1118	0.0827	0.0746	0.0850
	0.0862	*0.0640*	*0.0794*	*0.0943*	*0.1073*	*0.1225*	*0.0179*	*0.0304*	*0.0176*	*0.0126*	*0.0146*	*0.0259*
Middle	0.0481	-0.3156	0.1293	0.2653	0.3020	0.0674	0.1612	0.1401	0.1916	0.1493	0.1554	0.1386
	0.1018	*0.3021*	*0.1261*	*0.0948*	*0.0850*	*0.2273*	*0.0201*	*0.0299*	*0.0217*	*0.0223*	*0.0161*	*0.0268*
Matric	0.1592	-0.0811	0.1733	0.3696	0.3495	0.2112	0.2126	0.2743	0.2330	0.1804	0.1629	0.1644
	0.0703	*0.1319*	*0.0685*	*0.0542*	*0.0543*	*0.0893*	*0.0183*	*0.0225*	*0.0156*	*0.0110*	*0.0153*	*0.0258*
Intermed	0.1672	0.0058	0.2425	0.3988	0.3731	0.1764	0.3425	0.3584	0.2986	0.2651	0.2833	0.3235
	0.0813	*0.2684*	*0.0692*	*0.0560*	*0.0660*	*0.0871*	*0.0241*	*0.0319*	*0.0144*	*0.0177*	*0.0234*	*0.0265*
Graduate	0.5336	0.3963	0.4503	0.5798	0.6475	0.6033	0.5563	0.4560	0.4520	0.4748	0.6412	0.6538
	0.0816	*0.1336*	*0.0473*	*0.0514*	*0.0693*	*0.1296*	*0.0282*	*0.0225*	*0.0275*	*0.0179*	*0.0337*	*0.0411*
post_pro	0.9052	0.4799	0.7352	1.0898	1.2464	1.1287	0.8035	0.5842	0.7150	0.7983	0.8449	0.8712
	0.0922	*0.1084*	*0.0825*	*0.0609*	*0.0815*	*0.0973*	*0.0319*	*0.0384*	*0.0208*	*0.0228*	*0.0275*	*0.0469*
Public	0.4763	0.9651	0.8268	0.4308	0.1363	0.0753	0.0086	0.2280	0.1057	-0.0102	-0.0967	-0.1626
	0.0542	*0.1055*	*0.0583*	*0.0622*	*0.0518*	*0.0522*	*0.0143*	*0.0177*	*0.0125*	*0.0082*	*0.0099*	*0.0194*
Urban	0.0797	0.1373	0.0776	0.0688	0.0882	0.1559	0.1329	0.1068	0.1190	0.1369	0.1255	0.1386
	0.0436	*0.0647*	*0.0545*	*0.0285*	*0.0351*	*0.0499*	*0.0120*	*0.0153*	*0.0074*	*0.0099*	*0.0125*	*0.0203*
white_c	0.1747	0.2571	-0.0414	0.0457	0.1668	-0.0680	0.4385	0.4187	0.3509	0.3345	0.4550	0.5659
	0.1008	*0.2858*	*0.1103*	*0.0545*	*0.1884*	*0.1569*	*0.0436*	*0.0740*	*0.0406*	*0.0402*	*0.0550*	*0.0675*
blue_c	0.0281	0.1775	-0.1175	-0.0172	0.0823	-0.1541	0.2450	0.3517	0.2666	0.1863	0.1816	0.1593
	0.0845	*0.2444*	*0.1023*	*0.0500*	*0.1995*	*0.1302*	*0.0386*	*0.0719*	*0.0366*	*0.0418*	*0.0432*	*0.0535*
_cons	6.2552	4.6553	5.9034	6.1893	6.7388	7.4740	6.1286	4.8185	5.7995	6.4141	6.8574	7.2085
	0.1378	*0.3371*	*0.1706*	*0.1121*	*0.2551*	*0.2759*	*0.0529*	*0.1409*	*0.0542*	*0.0669*	*0.0678*	*0.0923*
Adj R-squared	0.3644	0.1856	0.259	0.2976	0.2486	0.2604	0.2698	0.1932	0.1775	0.1735	0.2028	0.2312
Number of Obs	1365	1365	1365	1365	1365	1365	12229	12229	12229	12229	12229	12229

Note: Standard errors are in italics. The OLS standard errors are based on Huber (1967) and the quantile regression model estimates are based on bootstrapping.

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